

Post-processing forecasts from a convectivepermitting weather model for national flow forecasting

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HEPEX 2018, Melbourne, Australia, 6th-8th February 2018

enhancing the benefits of New Zealand's natural resources



Water in New Zealand



Stuff International tourism overtakes dairy to regain top spot as our biggest export earner



Towards a national flow forecasting system



Weather model: general performance

Cloud-resolving model gives a much more realistic annual mean rainfall distribution



Observed data at NIWA



¹ Woods, R.A.; Hendrikx, J.; Henderson, R.D.; Tait, A.B. 2006: Estimating mean flow of New Zealand rivers. Journal of Hydrology (NZ), 45(2): 95-110.

Station data at NIWA



Aim – National forecast precipitation calibration



Weather Forecast 1.5km, hourly

Gridded observed data 5km, daily

Daily data Hourly forecasts

Case study:

- 3 year forecast archive
- 12 stations (hourly) elevation 42m-1022m



Rainfall post-processing

Approach #1: Baseline – Hourly data

- Baseline
- Calibration using hourly data

Approach #2: Pseudo-hourly data

- Daily data
- Hourly disaggregation:
 raw forecast (rain)
 - o divide by 24h (no rain)
- Calibration using pseudohourly data

- Daily data
- Calibration using daily data
- Hourly disaggregation:
 - Historical raw forecasts



Bayesian rainfall forecast post-processor

(Robertson, Shrestha, Wang, 2013, HESS)

Step 1: Correct biases and quantify uncertainty

Simplified Bayesian joint probability (BJP) model (Wang et al 2009)

- Log-sinh transformation (Wang, Shrestha, Robertson, Pokhrel, 2012, WRR)
- Continuous bivariate normal distribution
- Treatment of zero data (Wang and Robertson 2011)

Step 2: Instill temporal and spatial patterns

Schaake Shuffle (Clark, Gangopadhyay, Hay, Rajagopalan, Wilby, 2004, JHM) Template data: historical observed data



Hourly forecasts



Lead time hour ightarrow



Bayesian rainfall forecast post-processor

Step 1: Correct biases and quantify uncertainty



Last 24h m=1000

Step 3: Hourly disaggregation and combine overlapping forecasts



Results

Approach #1: Baseline – Hourly data Approach #2: Pseudo-hourly data

Results – Total daily precipitation (1-24h)

Ensemble ranges and observations versus ensemble mean





Forecast too low

0.75 Too wid

Results – Reliability of daily total precipitation (1-24h)

Results – Hourly disaggregation

Percentage bias per lead time



Results – Hourly disaggregation



Lead time (hrs)

Results – Hourly disaggregation



Results – Summary

Approach #1: Baseline – Hourly data

- Ideal case
- Removed bias
- Reliable ensemble

Approach #2: Pseudo-hourly data

- Removed bias
- Larger errors cumulate daily
- Forecast a little narrow, too much temporal correlation?

- Removed bias
- Smaller ensemble ranges
- Reliable ensemble (daily totals)
- Edge effects ⊗



Conclusions

1. National flow forecasting system for New Zealand



2. BJP rainfall post-processing: Daily data and hourly forecasts



3. <u>Refine approach</u>: Combine daily and pseudo-hourly approaches?

Thank you!

